Application of Soft Computing Techniques for Non-linear Process Modelling

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***Abstract*— This paper deals with various soft computing techniques for modelling non-linear system. The traditional well established methods of modelling fail to describe non-linear system accurately. In this paper soft computing techniques like fuzzy, neural network and neuro fuzzy are used to model Conical Tank System (CTS). CTS has nonlinearity due to its shape. Models obtained using soft computing techniques proved to be well accurate with minimal model mismatch. The validity of the models is compared by taking mean-square error as performance criteria. ANFIS model for the systems produced superior results with minimum Root Mean Square Error (RMSE).**

***Index Terms* — ANFIS (Adaptive Neuro Fuzzy Inference System), CTS (Conical Tank System), T-S Fuzzy model, Neural network model, RMSE(Root Mean Square Error)**

I. INTRODUCTION

Almost all the processes are non-linear in nature. Modelling of a non-linear system is very essential to develop an effective control system. Developing mathematical models of non-linear systems is a central topic in many disciplines of engineering. Models can be also used for simulation, analysis of system's behaviour, better understandings of the underlying mechanisms in the system, design of new process and design of controllers [4]. In a control system the plant displaying non-linearity has to be described accurately to design an effective controller [13].

Obtaining mathematical model of a complex non-linear system using conventional modelling techniques is complex and time consuming as it often requires some assumptions and linearization [11]. Also mathematical model results in highly non-linear differential equation which should be linearized afterwards to form transfer functions. These approximations can result in performance degradation in the obtained model and in designed controller too.

The neural network training algorithm for feed forward networks used is Levenberg-Marquardt (LM) algorithm [1].The extraction of compact fuzzy rules for non-linear system modelling using subtractive clustering and genetic algorithm is given in [2]. Various data driven methods using clustering algorithms are discussed in [7][8][12]. A new parameter identification method of MIMO non-linear systems using both LM optimization and least square method for fuzzy models is given in [3]. The fuzzy rule structure identification and optimization of consequent and premise parameters without any assumption of data structure is developed in [6]. First an initial structure is formed and improved. And tuning of fuzzy rule parameter will be done. The loop of structure improvement and retuning of rule parameters continues till a satisfactory Takagi Sugeno Kang (TSK) model is found.

The application of T-S fuzzy model in adaptive fuzzy control scheme is given in [14]. The parameter estimation scheme for updating the parameters of T-S fuzzy models is analyzed based on the Lyapnov theory. A strategy is developed to optimally tune constrained predictive controller of MIMO non-linear system with T-S fuzzy model approach [18].

The effectiveness of ANFIS in adaptive learning through hybrid algorithm and basic ANFIS structure is given in [10]. The suitability of ANFIS in multi-criteria decision making problems is given in [17]. The proposed method considered linear regression analysis and MSE as the performance indices as in [16][9]. The application of ANFIS in speed control of induction motor is given in [5].

II. CONICAL TANK SYSTEM

CTS is a bench mark problem for recent research studies. CTS is a SISO non-linear process in which non-linearity is due to its shape. It imitates the non-linear nature of many industrial processes. CTS has an inverted conical tank with top inlet flow given by F_{in} and bottom outlet flow given by F_{out}. The liquid level 'h' of conical tank is considered as the measured variable or output variable. The inflow rate 'F_{in}' is manipulated using a control valve with coefficient k_v to obtain the required level in the tank. The schematic diagram of conical tank system is given below.

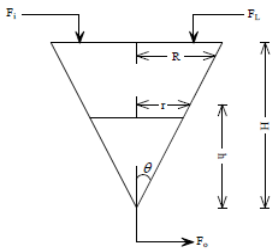

Fig. 1. Schematic Diagram of Conical Tank System

III. T-S FUZZY MODELLING

The proposed methodology models the non-linear systems as T-S fuzzy model which allows the reduction of number of rules compared to Mamdani model. The consequent part of IF-THEN fuzzy rule is replaced by a linear equation in T-S fuzzy modeling. A set of linear equations of input variables are formed from given input output data. The fuzzy rules represent local input-output relation of non-linear systems. Then the overall fuzzy model of the system is obtained by fuzzy blending of linear models. Fuzzy modelling is based on knowledge expertise and it provides a transparent modelling technique. The T-S fuzzy rule is given by,

If x is A and y is B, then u = f(x,y)

where A and B are fuzzy sets mapped to membership functions in the antecedent part, and u = f(x,y) is a linear function in the consequent part. f(x,y) is linear equation of input variables x and y.

The parameter identification of fuzzy model is done using fuzzy c-means and subtractive clustering.

a. Fuzzy C-means Clustering (FCM)

FCM clustering is a clustering method in which the clusters centers are randomly initialized. It allows the inclusion of each data point to multiple clusters with different membership degrees. The clustering is based on the minimization of objective function given by

$$J_m = \sum_{i=1}^{D}\sum_{j=1}^{N}\mu_{ij}^{m}\left|\left|x_i - c_j\right|\right|^2 \qquad (1)$$

where D is the number of data points, N is the number of clusters m is fuzzy partition matrix exponent which controls the degree of fuzzy overlap, with m > 1. x_i is the ith data point ,c_j is the centre of the jth cluster. μ_{ij} is the degree of membership of x_i in the jth cluster.

b. Subtractive Clustering

In subtractive clustering each data point is assumed as a potential cluster center. Based on the density of surrounding data points, a measure of likelihood of each data point with the potential cluster center is calculated. Similarly the potential of every data point is calculated and the one with highest potential is selected as the first cluster center. Then the potential of each data point is revised by subtracting an amount of potential from each data point as a function of its distance from the first cluster centre. The nearer data points will have minimum revised potential compared to the farther ones and are unlikely to be selected as the next cluster centre. After the revision of potential of all data points, the one with highest remaining potential will be selects as the next cluster centre. This process continues until a sufficient number of clusters are obtained [8].

IV. NEURAL NETWORK MODELLING

Neural network consists of highly interconnected processing elements working in unison to solve specific problems.

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used for modelling of complex non linear systems in process control. Here the real time input output data is collected from the non-linear systems and is used to train the neural network using LM back propagation algorithm.

a. Levenberg-Marquardt Back Propagation Algorithm

LM back propagation algorithm trains the neural network by updating weights and bias values using LM optimization. It is the fastest back propagation algorithm which trains neural networks at a rate 10 to 100 times faster than gradient descent back propagation method. It does not require more memory compared to other algorithms. It works without the computation of Hessian matrix. When the performance index or function assumes the form of sum of squares then the Hessian matrix can be approximated as $H = J^TJ$. Then the gradient of error vector can be computed as $g = J^Te$. Here J is the Jacobian matrix containing first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. A standard back-propagation technique can be used to compute J. The LM algorithm uses this approximation to the Hessian matrix in the Newton-like update equation given by

$$x_{k+1} = x_k - [J^TJ+\mu I]^{-1}J^Te \qquad (2)$$

The above equation just approximates Hessian matrix when μ is zero. And it becomes gradient decent with a small step size when μ is large. μ will be decreased for the decrease in the performance function for each step and is increased only when the performance function is tentatively increased in the next step. Thus performance function is reduced for each iteration of the algorithm

V. ANFIS MODELLING

ANFIS is a data learning technique that uses the advantages both fuzzy and neural networks An ANFIS works by applying neural network training methods to tune the antecedent and consequent parameters of a fuzzy inference system. ANFIS uses a hybrid learning algorithm which integrates the gradient descent method and least square methods to train parameters [10]. In the forward pass of algorithm, signals go forward until layer 4 and the consequent parameters are identified by least squares method to minimize the measured error. In the backward pass the premise parameters are updated by gradient descent method. Here initial Fuzzy Inference System (FIS) generated using FCM, subtractive clustering and grid partitioning are trained using ANFIS. FCM and subtractive clustering is done as per the procedure given in section IV.

a. Grid Partitioning

The fuzzy rules can be generated using fuzzy grids from the system input-output training data. The performance of the obtained fuzzy model solely depends on the definition of the grid. The performance increases as the grids become finer.

The optimization of performance and refinement of grid partition can be done using adaptive grid partitioning. In adaptive approach a uniformly partitioned grid is used for initialization. The adaptive process adjusts parameters of antecedent membership functions and the fuzzy grid evolves. To optimize size and location of fuzzy grid regions and the overlapping degree among them gradient descent can be used. The major drawback of this grid partition method is that the performance suffers from an exponential explosion of the number of inputs or membership functions as the input variables increase.

VI. SIMULATION RESULTS

The modelling of CTS is done by collecting the system input-output data. The input parameter is input flow rate in lph and output parameter is level in cm. In CTS as the non-linearity is due to the tank's shape, the area for each level is also considered for training. The results of neural, fuzzy and ANFIS modelling is given below.

Neural Network Model Output

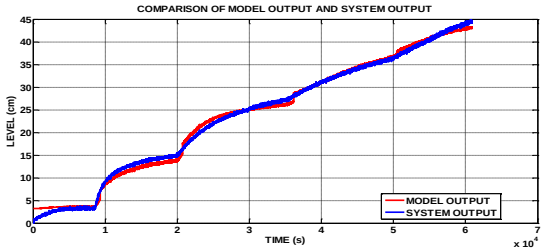

Fig. 2. Comparison between neural network model output and CTS output

Fuzzy Model Outputs

In fuzzy modelling, the initial FIS is obtained by using Fuzzy C-means and Subtractive clustering. The membership functions generated in both the cases are Gaussian MFs. FCM clustering has more RMS error compared to subtractive clustered one and also it is inconsistent in its results. It also required further training using ANFIS to improve its performance. Computational time taken in FCM is less than subtractive, but the difference is minute. Subtractive clustered FIS shows less RMS error but computational time taken is more than FCM.

a. Fuzzy Model Output Using FCM Clustering

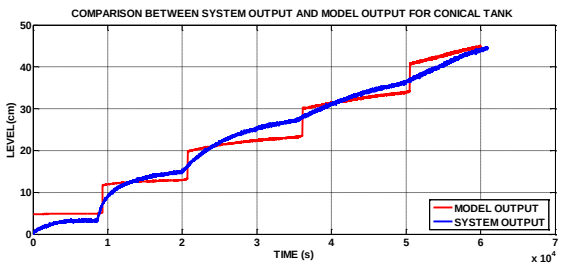

Fig. 3. Comparison between FCM clustered fuzzy model output and CTS output

b. Fuzzy Model Output Using Subtractive Clustering

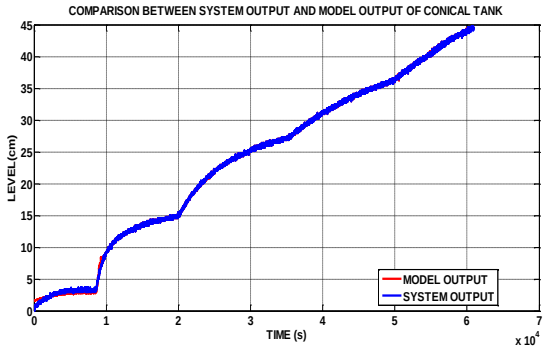

Fig. 4. Comparison between subtractive clustered fuzzy model output and CTS output

ANFIS Model Outputs

In ANFIS modelling, three methods were used to generate initial FIS namely grid partitioning, subtractive clustering and also by providing training for FCM clustered FIS. Grid partitioning took very high computational time but provided more accurate results than other two methods. When ANFIS training was provided to FCM clustered FIS, its RMS error was reduced even less than that of subtractive clustering. Subtractive clustered FIS produced more or less same RMS error before and after ANFIS training, but with the same computational efficiency. Here also MFs generated were Gaussian MFs. It produced least error than any other MFs.

a. ANFIS Output for Grid Partitioned FIS

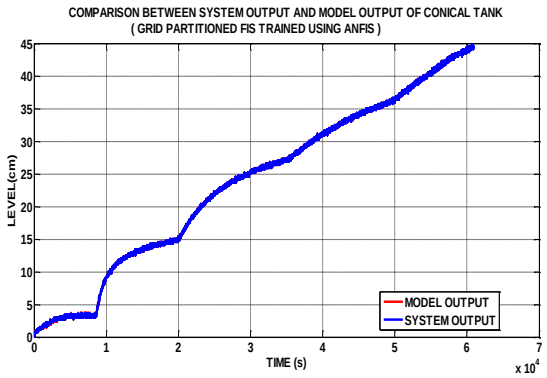

Fig. 5. Comparison between grid partitioned ANFIS model output and CTS output

b. ANFIS Output for FCM Clustered FIS

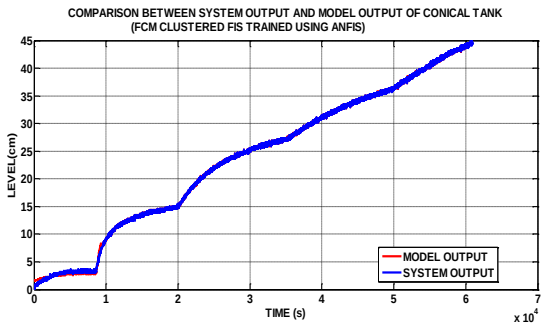

Fig. 6. Comparison between grid FCM clustered ANFIS model output and CTS output

c. ANFIS Output for Subtractive Clustered FIS

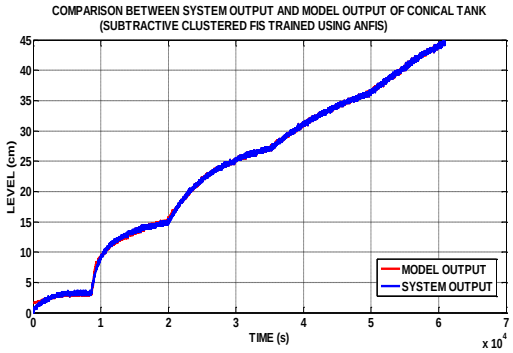

Fig. 7. Comparison between subtractive clustered ANFIS model output and CTS output

TABLE I: Membership Functions of Fuzzy and ANFIS Modelling

Method Used	RMS Error
Neural Network	0.1732
Fuzzy (FCM clustering)	0.8810
Fuzzy (Subtractive clustering)	0.2201
ANFIS (Grid)	0.0323
ANFIS (FCM)	0.1395
ANFIS (Subtractive clustering)	0.1642

TABLE II: Performance analysis using RMSE for CTS

Modelling Method	Number of Gaussian Membership Functions	
	Input 1	Input 2
Fuzzy FCM Clustering	5	5
Fuzzy Subtractive Clustering	8	8
ANFIS FCM Clustering	5	5
ANFIS Subtractive Clustering	8	8
ANFIS Grid Partitioning	10	10

VII. CONCLUSION AND FUTURE SCOPE

It is generally impossible to obtain an accurate approximation of systems, having non-linearities . The controller design will get more complicated in the absence of a reliable model. Thus the system with desired output and stability cannot be realized. The results showed that by using soft computing techniques non-linear systems can be efficiently modelled. The accuracy of the models lies in selection of input and output parameters. The input-output data should possess the process characteristics of the system for it to be exactly modelled. ANFIS having the advantage of both fuzzy and neural networks had minimum RMSE. The models developed can be used for implementation of model based controllers to obtain robust controller performance. Model developed can be used for fuzzy control schemes, internal model based control schemes etc.

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